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Modeling Bat's Sonar System using a Microcontroller

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***Abstract*— Maxbotix Sonar sensors use ultrasound frequency of 42kHz to measure distance to an object similar to bats natural Sonar use to detect prey or food. All sensors have some form of noise or errors in their measurements and the main objective is to eliminate or reduce much of it. In some applications the measurement readings contain fluctuating noise more than others. In such a case, the Kalman filter is used to filter out the noisy readings. The Kalman filter is implemented on an Arduino microcontroller connected to a Sonar sensor. An application is presented to study the practical aspects of Kalman filter implemented on a open source microcontroller in real-time.**

Keywords-Arduino; Kalman Filter; Sonar; microcontroller.

I. INTRODUCTION

In nature, bats have one of the most sophisticated natural Sonar (SOund wave Navigation And Ranging) system. They have the ability to perform continuous tracking to their prey. Their tracking system is a continuous monitoring of range, position, and velocity of a target in space from their current position in space [1]. There are numerous species of bats with variety of sizes and weights ranging from 2 grams to 1 kg. Bats use echolocation to detect [2] There are many different species of bats and emit a very loud sound pulses and listen for the echoes that bounce back from surrounding objects. Each pulse is short in duration up to 8 to 10 ms with a constant frequency in range of 25 kHz to 150 kHz. The bats emit anywhere from 10 to 20 sound bursts every second. The amazing part is as they home on to the prey the rate of pulse emission increases to about 200 pulses per second. Also fascinating part is that they are capable of building a 3 dimensional image of the surrounding, be able to calculate distance and orientation of the target, and moving speed of the flying insects. When a prey is found, the pulse emission rate increases to 200 pulses per second [3]. Fig 1 shows an actual bat in action of catching its prey.

The interesting part is their signal processing capabilities. Humans learn from nature and try to mimic nature how to use sound waves to detect, and locate objects. Our objective is to use Sonar sensors, with Arduino microcontroller board to localize a stationary object or a moving object in a straight line with constant velocity. As all sensors have some form of noise (errors) in their measurements. Sound waves travel through the air medium to the ears. All animals including humans use their ears to hear and depending on the intensity of the sound can locate the direction of the sound. Other than bats, such as whales and dolphins also use sound to see by emitting sounds that reflect off objects and return back to their ears [3]. These animals can determine the direction and location of an object by knowing how long it takes the sound to reach their ears. By nature the ears of the bats are created to receive sound and with their two ears helps them triangulate the location of objects. The reflected sound arrive at different times and different speeds to each ear. Therefore, with the delayed arrival of the sound waves to the bats ear they can predict the size and can triangulate objects. Many researchers have studied bats and in particular have looked in the following features: frequency of the call, at which Hertz the call is made, constant frequency or frequency modulation, intensity of the chirp (loudness of the sound, either low to high or high to low), increase in the chirps as the bat hones in on the prey, creation of multiple frequencies in a chirp with one dominant frequency, duration of the chirps and the time between the chirps [14].

Sonar sensors can be used to interact with the physical world and using a USB cable to the Arduino microcontroller can be connected to a computer and programmed using the C programming language. Arduino is an inexpensive open-source microcontroller designed to facilitate interaction with the physical world. There are a variety of sensors and shields (boards) that may be used to interact with Arduino for a variety of applications. As the Sonar sensor's range measurements contain noise, the Kalman filter is employed to reduce the noise. Arduino microcontroller reads values from the Sonar sensor which are contaminated with noise. The MaxBotix Sonar sensors are used in a wide variety of applications. The sensor operates at 42kHz sound waves [13]. The ultrasonic waves at certain frequencies can pass through solid objects and can be made to detect only specified materials. The 42kHz ultrasonic frequency allows the sensor to detect sold and liquid medium. At this frequency of 42kHz sound waves get reflected from any object and are detected, even porous and non-solid objects can be detected by the sensor. The MaxBotix sensor was chosen as its performance is reliable and fairly accurate when operated in air medium. Ultrasonic sensors are used in many applications such as liquid level control, solar powered applications, people detection, tank level measurement, mobile robotics, and many others. Some targets can absorb more sound are more difficult to detect with the 42kHz sensors. The reflection of sound is like reflection of light, as every object reflects different colors of light. Sound is reflected off differently from different objects. Porous targets such as dust, snow, people, and cloth do not reflect sound well due to small pockets of air which cause the sound to dissipate. Nonporous and smooth surfaces reflect sound well, such as glass, sheet metal, finished wooden surfaces and even water [13].

The paper is organized as follows, in Section II, the methods are presented. In section III, the experimental setup is presented and in section IV results and discussions are presented and finally in section V, conclusion and future directions are given.

Figure 1. Bat in action catching prey.[2]

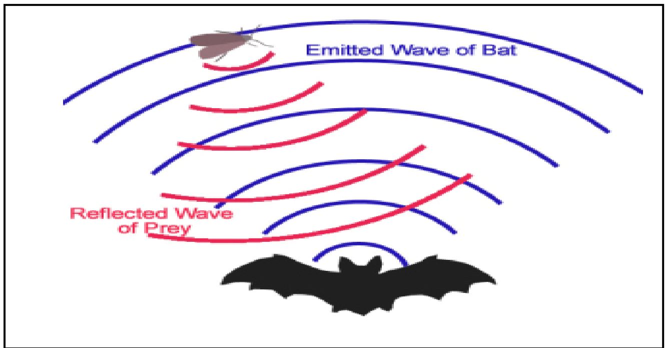

Figure 2. Bat echolocation of prey. *[9]*

TABLE I. BAT SONAR CHARACTERISTICS

	Characteristic	Bat sensor
1	Frequency Range	12kHz to 200kHz
2	Pulse Width	Milliseconds
3	Navigation and Obstacle Avoidance	Sense wires as thin as 0.3mm in diameter
4	Detection Range	5 m to 30 m
5	Range Resolution	30 mm
6	Multi-Mode	Search and track
7	Monopulse	Yes
8	Doppler Tracking	Yes

II. METHODS

The Kalman Filter is a very useful tool for stochastic estimation from noisy sensor measurements. The Kalman Filter was developed by Rudolf E. Kalman, in 1960 he published a paper describing a recursive solution to the discrete data linear filtering problem. The Kalman filter is a predictor - corrector type of estimator and it minimizes the estimated error covariance [4], [5], [12], [17]-[20],. In this section, the Kalman filter is presented to filter out the noise from the Sonar readings. When the linear dynamic system is corrupted by Gaussian white noise the Kalman filter gives the best estimate in the least mean square sense. The Kalman filter is used to estimate the state x of a linear controlled process given as,

$$\mathbf{x_k} = \mathbf{A}\,\mathbf{x_{k-1}} + \mathbf{B}\,\mathbf{u_k} + \boldsymbol{w_{k-1}} \tag{1}$$

and a measurement model that describes the relation between the states and measurements is given by

$$\mathbf{z_k} = \mathbf{H}\,\mathbf{x_k} + \boldsymbol{v_k} \tag{2}$$

where w_k and v_k are random variables representing the process and measurement noise, respectively. They are assumed to be Gaussian and independent of each other with zero mean. The noise covariance Q of the process and noise covariance R of the measurement noise matrices are time dependent. The matrix A is an n x n matrix and relates the state at the previous time step k-1 to the state at current time step k. The matrix B is n x q and relates the control input u to the state x. The matrix H is m x n relates the state to the measurement z_k. Generally, all the matrices A, B, H, Q, R, are time dependent, however are assumed to be constant in the work presented here. The Kalman filter consists of two groups, one is the time update equations and the other is the measurement update equations. The time update (Predict) equations are the following:

<u>Time update (Prediction)</u>

Step 1: Predict the state x

$$\mathbf{x_k} = \mathbf{A}\,\mathbf{x_{k-1}} + \mathbf{B}\,\mathbf{u_k} \tag{3}$$

Step 2: Predict the process error covariance

$$\mathbf{P_k} = \mathbf{A}\,\mathbf{P_{k-1}}\,\mathbf{A^T} + \mathbf{Q} \tag{4}$$

Equation (3) is the predicted (a priori) state and eq (4) is the predicted (a priori) estimate covariance.

The measurement or correction update equations are used in the feedback and consist of the following equations,

<u>Measurement Update (Correction):</u>

Step 1: Compute Kalman gain

$$\mathbf{K_k} = \mathbf{P_{k-1}}\,\mathbf{H^T}\,(\mathbf{H}\,\mathbf{P_{k-1}}\,\mathbf{H^T} + \mathbf{R})^{-1} \tag{5}$$

Step 2: Update estimate using measurement z_k

$$\mathbf{x_k = x_{k-1} + K_k (z_k - H\, x_{k-1})} \qquad (6)$$

Step 3: Update process error covariance

$$\mathbf{P_k = (I - K_k\ H) P_{k-1}} \qquad (7)$$

where $\hat{x}$ is the estimated state, A is the state transition matrix, u is the control variables, B is control matrix, P state variance matrix, Q process variance matrix, y measurement variables, H is measurement matrix, K is the Kalman gain which minimizes the a posteriori error covariance. Note when the measurement error covariance R --> 0 the gain K weights the residual more heavily, whereas when the a priori estimate error covariance P_k goes to zero the gain K weights the residual less. In other words, as the measurement error covariance R approaches zero, the actual measurement z_k is trusted more while the predicted measurement Hx_k is trusted less, whereas as the a priori estimate error covariance P_k approaches zero the actual measurement z_k is trusted less and the predicted measurement Hx_k is trusted more.

Equation (5) is called the innovation or measurement residual, and indicates the difference between the actual measurement by the sensor and the predicted measurement Hx_k. Note when the difference is zero is an indication of complete agreement. eq (6) is the innovation (or residual) covariance, eq (7) is called the Kalman gain, eq (8) is the updated (a posteriori) state estimate and eq (9) is the updated (a posteriori) estimate covariance.

A. Case stationary object.

The state vector is the output readings from the Sonar x(t) and assume the object is stationary (fixed location), therefore A = 1, there is no control input to the system, hence B = 0, output of the Sonar is the only observables, hence H = 1, and the process noise is assumed to have covariance Q. The Kalman equations can now be written as;

Predictor :

Predict the next state: $\mathbf{x_k = x_{k-1}}$

Predict next covariance: $\mathbf{P_k = P_{k-1} + q}$

Estimator (correction):

Compute Kalman Gain: $\mathbf{K = P_k / (P_k + R)}$

Update state estimate: $\mathbf{x_k = x_{k-1} + K * (m_k - x_{k-1})}$

Update covariance estimate: $\mathbf{P_k = (1 - K) * P_{k-1}}$

B. Case object linearly moves at constant rate toward or away from stationary Sonars

In this case, a an object is being either approaching or moving away at a constant rate. The process is modeled as,

$$\boldsymbol{d = d_{initial} + r}$$

where $\boldsymbol{d}$ is the distance, and $\boldsymbol{r}$ is the rate at which it is moving.

The state $\mathbf{x} = (x_d,\ x_{rate})^T$

and the state transition matrix is

$$F = \begin{bmatrix} 1 & dt \\ 0 & 1 \end{bmatrix}$$

The measurement matrix H sifts out only the distance

$\mathbf{H = [\,1\ ,\,0\,]^T}$

$\mathbf{z} = [\,z, \mathbf{0}\,]^T$ is the estimated measurement of x_d,

The noise is assumed to be q_r, then the Q variance matrix is

$$Q = q_r \begin{bmatrix} 1/3 & 1/2 \\ 1/2 & 1 \end{bmatrix}$$

and the state covariance matrix is

$$P = \begin{bmatrix} P_h & P_{hr} \\ P_{hr} & P_r \end{bmatrix}$$

C. Case object linearly moves at constant rate left or right and motor rotates anti-clockwise or clockwise

Two Sonars are placed on each end of a straight stick and the stick mounted on a motor such that the motor can rotate the stick holding Sonars either clockwise or anti-clockwise directions. The objective is to rotate the motor clockwise or anticlockwise such that the reflected waves from the object to the Sonars produce the same range reading. The same readings at both Sonars would then indicate the object is now localized. This is similar to a bat's ears being focused toward the direction of the prey.

There are three cases:
Case A: measurement A - measurement B < tolerance indicating object direction is equidistance from each Sonar where tolerance is chosen to desired accuracy of direction. Ideal case would be a difference value of zero, in practice not possible to achieve. For example, choosing a value of 0.2 for tolerance gives more a directional precision than choosing a value of 0.6.

Case B: measurement A - measurement B > threshold indicating rotate motor clockwise.

Case C: measurement A - measurement B < threshold indicating rotate motor anti clock-wise.

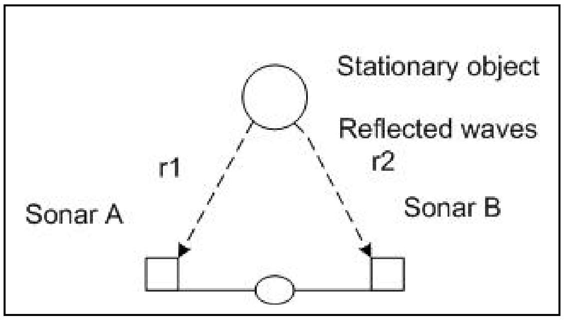

Figure 3. Two Sonars A and B mounted on a motor pointed toward object at center giving equal reflection.

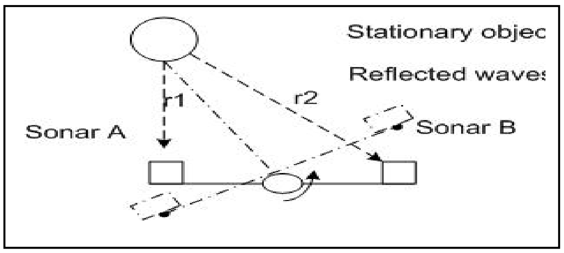

Figure 4. Two Sonars A and B mounted on a motor are rotated anti-clockwise direction to focus on stationary target object.

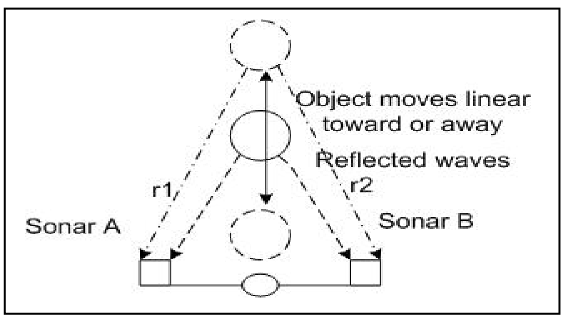

Figure 5. Object moves linearly toward or away from with constant rate.

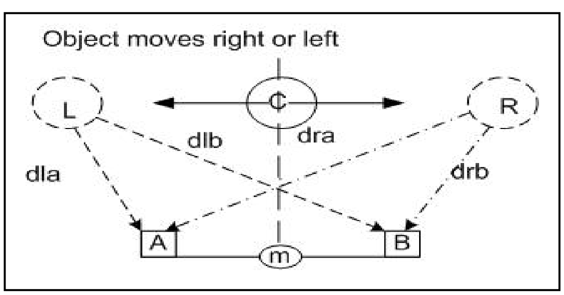

Figure 6. Object moves linearly right or left with constant rate.

III. EXPERIMENTAL RESULTS AND DISCUSSION

Maxbotix Sonars, with stepper motor, and arduino micro-controller board were used in the experiment setup. The Sonars were used to localize the object and measure the range. Sonar sensors have been applied in various applications, such as navigation, human detection, robotics, tank level measurments, and many others [14]. The Sonar used in the experiments uses the 42kHz frequency to detect an object by transmission of sound waves which reflect off the object and the surroundings. The distance is calculated by using the time of flight properties the speed of wave traveling and wavelength. The sensor can use any of the three outputs, the analog voltage, pulse width, and RS232 serial.

The Arduino Uno microcontroller was used to read the Sonar measurments on analog pin number 0 and pin 1. The stepper motor was used to rotate the Sonar sensors toward the object. Since, the Sonar distance measurement are noisy, the Kalman filter was used to remove the noisy part and provide a more smoothed and accurate measurement. In the first experiment, an object moves either toward or away at a constant rate from a stationary Sonar. In other words, the object is centered and movement is perpendicular to the Sonars mounted on a straight beam.

The Maxbotix Sonars used have the following features [14], object detection to zero range objects, continuously variable gain for control and side lobe suppression, readings can be made every 50 mS, or 20 Hz rate, can continually measure and output range information, has a triggered operation provides the range reading as desired, interfaces are active simultaneously, has serial 9600 Baud, Analog Vcc/512/inch, and Pulse width, 147 uS/inch. [14]

The detection of an object depends on its diameter size and distance away from the Sonar. Each Sonar is manufactured with a specific beam width and capability of specific resolution from 1 inch to 1 or 2 mm [14]. Figure 9 shows the results of Kalman filter applied to the measurments received from a sonar with the object being stationary at a fixed distance. Figure 10 shows the results of Kalman Filter applied to Sonar readings when an object is moving away from stationary Sonar. It is seen the Kalman Filter lags the first 30 to 40 samples of measurements and then afterwards is able to keep on track to the true distance. Figure 11 shows the error in measurement and estimation. Figure 12 shows the prediction error covariance decreasing with increasing number of samples and then saturating to less than 0.01.

Figure 7. Maxbotix sonar used in experiments.

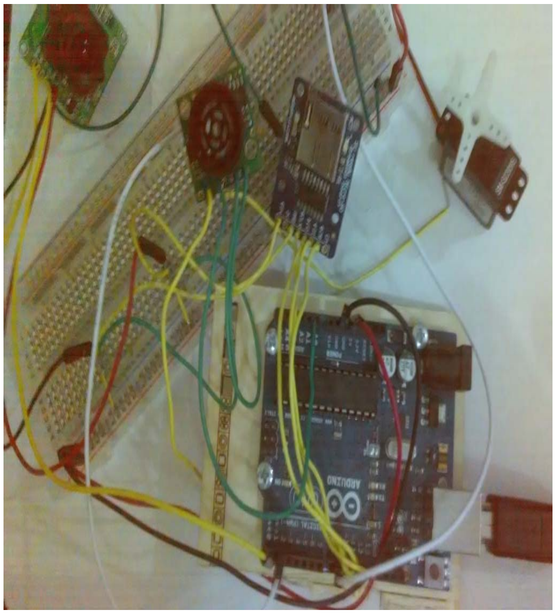

Figure 8. Arduino microcontroller with motor and sonars.

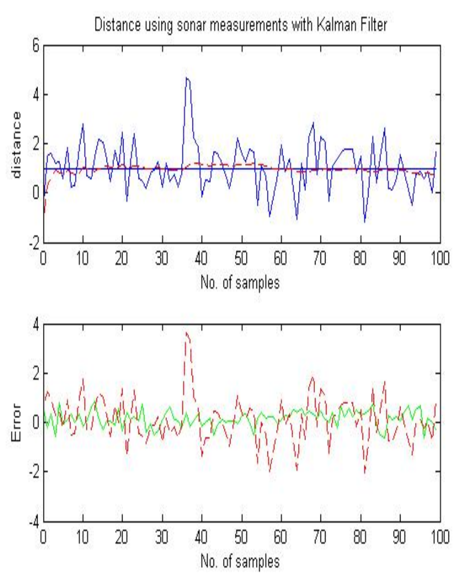

Figure 9. Results of Kalman fiter for a stationary object.

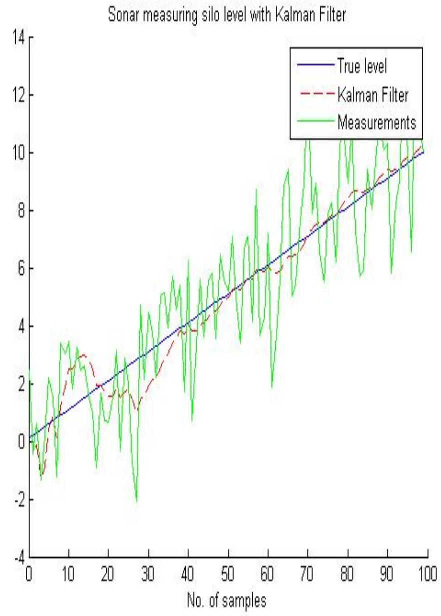

Figure 10. Kalman Filter results for object with constant rate.

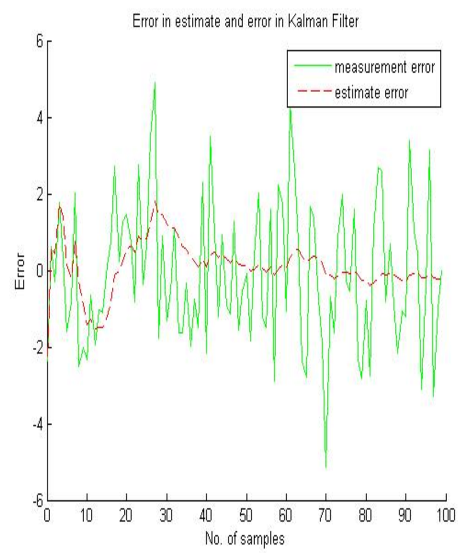

Figure 11. Measurement error and estimation error.

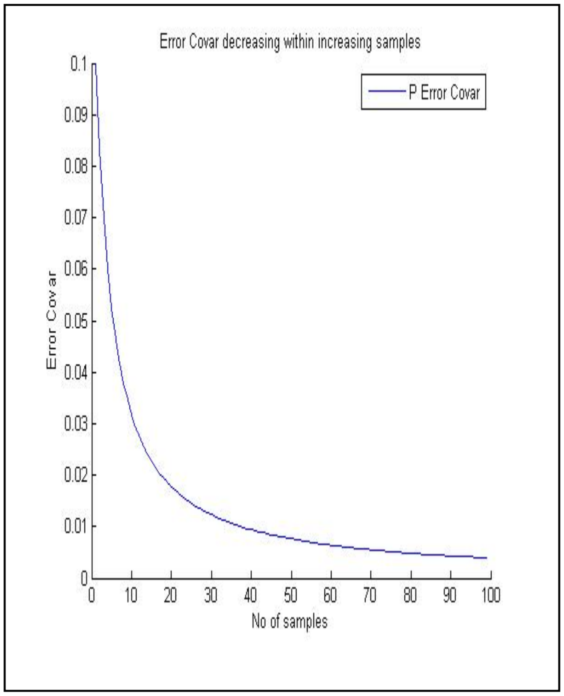

Figure 12. Prediction error covariance.

IV. Conclusion and Future Directions

It is seen bats' natural Sonar system can be modeled by mathematical models and implemented with Sonars, a motor and an open source Arduino microcontroller. As the measurements from the Sonar sensors contain unwanted noise the Kalman filter was used to filter out the noise and give more accurate measurements. Accurate measurements are needed to give precise direction toward an object. Once the precise direction is determined it then is possible to precisely move toward an object. In the future extension of work is use the results presented here in robotic arms and flying robots.

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